

Lessons from the Amazon Picking Challenge

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Abstract—This paper summarizes lessons learned from the first Amazon Picking Challenge in which 26 international teams designed robotic systems that competed to retrieve items from warehouse shelves. This task is currently performed by human workers, and there is hope that robots can someday help increase efficiency and throughput while lowering cost. We report on a 28-question survey posed to the teams to learn about each team’s background, mechanism design, perception apparatus, planning and control approach. We identify trends in this data, correlate it with each team’s success in the competition, and discuss observations and lessons learned.

Note to Practitioners: **Abstract**—Perception, motion planning, grasping, and robotic system engineering has reached a level of maturity that makes it possible to explore automating simple warehouse tasks in semi-structured environments that involve high-mix, low-volume picking applications. This survey summarizes lessons learned from the first Amazon Picking Challenge, highlighting mechanism design, perception, and motion planning algorithms, as well as software engineering practices that were most successful in solving a simplified order fulfillment task. While the choice of mechanism mostly affects execution speed, the competition demonstrated the systems challenges of robotics and illustrated the importance of combining reactive control with deliberative planning.

I. INTRODUCTION

The first Amazon Picking Challenge (APC) was held during two days at the 2015 IEEE International Conference on Robotics and Automation (ICRA) in Seattle, Washington. The objective of the competition was to provide a challenge problem to the robotics research community that involved integrating the state of the art in object perception, motion planning, grasp planning, and task planning to manipulate real-world items in industrial settings in the spirit of a long tradition of competitions as a benchmark for Artificial Intelligence [1] with the long-term goal of warehouse automation [2], [3]. This paper presents the results of a survey of the 26 teams that



Fig. 1. The RBO team’s robot placing a pack of Oreo cookies that it retrieved from the warehouse shelf into a tote. Image courtesy of RBO team.

participated in the challenge and synthesizes lessons learned by the participants.

The diversity of the solutions employed was impressive at a hardware, software and algorithms level. They ranged from large, single robot arms to multiple small robots each assigned to one bin on the shelf, from simple suction cups to anthropomorphic robotic hands, and from fully reactive approaches to fully deliberative sense-plan-act approaches. In surveying the details of each team’s approach and questioning them on what they learned from the experience, we hope to extract trends that help us (1) understand how to eventually solve the problem, and (2) discover what future robotics research directions are most promising for solving the general problems of perception, manipulation, and planning.

Extracting such trends, however, is not straightforward. Different teams got comparable results by following almost orthogonal approaches, sometimes stretching the limits of one technology as seen in Table III. Moreover, available data on successful grasps, i.e., removing a specific item from the bin and delivering it to a tote, is sparse, likely due to the numerous idiosyncratic ways that complex robotic systems can break down during a single evaluation trial outside of a lab environment. Still, it is possible to make some observations about the strengths and weaknesses of individual approaches, including both mechanisms and algorithms, and how they should be combined to improve the generality of solutions. We can also draw some conclusions about the process. For instance:

- some of the teams reported that they developed too many components from scratch and did not have time to make them robust,
- others reported that the off-the-shelf software components they used as “black-boxes” hid important functionality

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that could not be properly customized.

In this regard, there are important lessons about how to simplify the design of complex robotic systems and make them more reliable.

A. Outline of this paper

After providing more details on the competition in Sec. II, including scoring and rules, Sec. III provides the survey and its methodology. The results from the survey, broken into team composition, mechanism design, perception, planning, and summary questions, are described in Sec. IV. Sec. V then contains an analysis of the findings and lessons learned, which are discussed in Sec. VI and summarized in Sec. VII.

II. OVERVIEW OF THE COMPETITION AND RESULTS

The APC posed a simplified version of the task that many humans face in warehouses all over the world, namely, picking items from shelves and putting those items into containers. In the case of the APC, the shelves were prototypical pods from Kiva Systems¹ [4]. The picker was required to be a fully autonomous robot. Each robot had 20 minutes to pick twelve target items from the shelves.

The items were a preselected set of 25 products commonly sold on Amazon.com which would pose varying degrees of difficulty for the contestants' robots. The full set of items is shown in Figure 2. Simple cuboids, like a box of coffee stirrers or a whiteboard eraser, were among the easier items to pick. Larger items such as a box of Cheez-Its posed a challenge because it could not be removed from the bin without first tilting it. Smaller items, such as an individual spark plug, were more difficult to detect and properly grasp. The range of cuboid sizes was intentionally chosen to challenge traditional fixed-throw gripper designs that can operate only in a narrow range of possible object widths.

Beyond size, other items introduced challenges in perception and grasping due to other parameters, such as shape, deformation and the existence of transparent or reflective surfaces. For instance, unpackaged dog toys whose shape varied depending on how items shifted inside their collective packaging, or a pencil cup holder made of black wire mesh that foiled most sensors. Still other items were chosen because they were easy to damage, like two soft-cover books or a package of crushable Oreo cookies. The books introduced the additional challenge that they could potentially open after lifted from the bin with a vacuum gripper and then collide with the shelf during the retraction process. Objects with reflective covers are challenging for many depth sensors.

Only the central twelve bins on each pod were used for the contest in order to make the challenge compatible with the reach of the typical commercial armed robot. The organizers of the competition created five stocking arrangements in which the 25 products were distributed among the bins in such a way that each competitor had the same relative difficulty and the same potential to score 190 points. Ten minutes

before their trial, each competitor randomly selected one of the five stocking patterns, and the organizers spent the next few minutes arranging the shelf. The team was then given a *.json* file that described the contents of each bin (the names of the items in the bin), and a "work order" listing the twelve products that needed to be picked.

Pick target from 1-item bin	10 pts.
Pick target from 2-item bin	15 pts.
Pick target from 3+-item bin	20 pts.
Hard item bonuses	1-3 pts.
Drop target item	-3 pts.
Each item damaged	-5 pts.
Each non-target item removed	-12 pts.

TABLE I
THE APC SCORING RUBRIC WITH BONUSES FOR MORE DIFFICULT SITUATIONS AND PENALTIES FOR DROPPED OR WRONG ITEMS.

The scoring rubric is shown in Table II. Three of the bins had just the target item, six bins had a target item and one additional distraction, and the remaining three bins had a target and two (or more) distractions. In addition, some items that were projected to be more difficult to pick were given one to three bonus points each. Points were lost for damaging any item, picking the wrong item (and not putting it back), or dropping the target item anywhere but into the destination tote.

Designers of competitions aspire to create a task that is difficult enough to push the most advanced teams while being accessible to the rest of the field. Based on the results, shown in Table II, this was achieved in the Picking Challenge. The top team, RBO from the Technische Universität Berlin, picked ten correct items and one incorrect item, for a total score of 148 points. MIT placed second after picking seven items correctly for 88 points. Team Grizzly, a collaboration between Oakland University and Dataspeed Inc., placed third with 35 points and three successful picks.

Among all of the teams, a total of 36 correct items were picked, seven incorrect items were picked, and four items were dropped. About half of the teams scored zero points, including two who set up their robot, but did not get it working well enough to attempt the trials. There appeared to be a variety of reasons that teams did not perform well. For example, Team A.R. looked very promising in warm-ups, but the particular product arrangement they drew for the trial had the glue bottle alone in the lower left bin. Their system's planner computed a grasp plan that involved rotating the end-effector in such a way that the vacuum hose wound around the arm. They had not adequately modeled the hose behavior, and this one product in this particular bin exposed a corner case they had not seen during development and testing. Other teams failed because of last minute software changes, or failures to model the lip of the shelf such that the gripper had trouble finding a way into the bins. Lighting in the convention hall also proved to be a problem for some teams. For example, the Duke team resorted to taping an umbrella to the top of their robot to block overhead light.

With so few products picked overall, it is perhaps too early to draw meaningful conclusions. But we will offer up some

¹Kiva Systems was acquired by Amazon in 2012 and was rebranded Amazon Robotics around the time of this competition.



Fig. 2. Items used during the APC competition. Row-by-row starting from the top-left: Oreo cookies, spark-plug, whiteboard eraser, coffee stirrers, rubber ducky, crayola crayons, outlet protectors, sharpies, set of screwdrivers, safety glasses, Cheez-It crackers, set of 12 pencils, cat treats, glue, index cards, set of plastic cups, box of sticky notes, soft cover book, set of foam balls, dog toy, bottle cleaner, dog toy, soft cover book, pencil cup, dog toy. Numbers associated with some items are bonus points awarded for picking difficult items.

Team	Score	Correct	Wrong	Drops
RBO	148	10	1	0
MIT	88	7	0	0
Grizzly	35	3	1	2
NUS Smart Hand	32	2	0	0
Z.U.N.	23	1	0	0
C ² M	21	2	1	0
Rutgers U. Pracsys	17	1	0	1
Team K	15	4	3	1
Team Nanyang	11	1	0	0
Team A.R.	11	1	0	0
Georgia Tech	10	1	0	0
Team Duke	10	1	0	0
KTH/CVAP	9	2	1	0

TABLE II

THE FINAL APC SCORES. THE 13 TEAMS THAT SCORED ZERO OR NEGATIVE POINTS OR DID NOT ATTEMPT THE COMPETITION ARE NOT SHOWN IN THE TABLE.

observations. First, the product most commonly picked was the glue bottle, which was successfully picked seven times. This is in part due to the fact that it was alone in the bin in four out of five layouts, and paired with only one other product in

the fifth. In addition, the bottle was standing upright and was placed inside the bin relatively far from the walls, allowing easy access by grippers. Thus, it had the most favorable arrangements, provided good affordances for picking, and saw the most success. The package of Oreos and the spark plugs were also targeted in every layout. The cookies were successfully picked only three times (and dropped once) and the spark plug only once (and mis-picked once). The spark plug was in a box, but was still rather small. Surprisingly, the two soft-cover books were picked relatively often (three times each). Several of these picks involved attaching the suction to one cover of the book, which left the pages dangling. A potential complaint is that moving such items using this approach could potentially damage them.

The organizers and participants also ran into some rather mundane, but real-world problems. Despite the fact that 25 items were selected and pre-ordered before the competition, different instances of the same product looked rather different. The rubber duck, for example, sometimes was shipped in a plastic bag and sometimes not. The presence of the plastic bag had a dramatic impact on perception. Similarly, the plastic

cups did not always come with the same mix or stacking sequence of colors; sometimes the blue cup was on the outside and sometimes the red cup. Some manufacturers periodically change their product packaging; for example, there were two different sets of artwork for the crayon boxes. When these issues were identified during the competition, the teams were given a choice of which variant to use for their trial, but of course a real industrial system would need to handle these variations automatically.

III. SURVEY OVERVIEW AND METHODOLOGY

We administered an electronic survey a few weeks after the competition. The survey consisted of 28 questions that were grouped into five categories: “About your team”, “Mechanism”, “Perception”, “Planning and Control”, and “Summary Questions”. Within these categories, questions were geared towards understanding the composition of each team and its technical background, getting a comprehensive picture of the technical approach each team was using, listing open source tools that were deemed most important, understanding where most of the development effort was spent, and finding out what respondents thought the biggest challenges were. The survey was administered via surveymonkey.com and participants were invited by email.

We received 31 individual responses from 25 of the 26 teams, including Applied Robotics, Berkeley-Picker (2), C²M (2), CVAP, Duke, Georgia Tech (2), IntBot, MIT, Nanyang, Nuclear Robotics Group UT Austin, NUS Smart Hand, PickNik (4), Plocka Packa, Rutgers U. Pracsys, RBO, Research Center E. Piaggio, ROBINLAB UJI, Robological, SFIT, Grizzly, Team-K, University of Alberta Team, University of Washington, WPI, and Z.U.N. Numbers in parentheses behind each team correspond to the number of completed surveys received per team; for these teams, we checked all quantitative answers for consistency, and manually merged qualitative (text) responses. If quantitative responses were inconsistent, we averaged them. For example, if a team member replied “Neutral” to a question, and another “Strongly agree”, we averaged the team’s response to “Somewhat agree”, and used the value closer to “Neutral” for rounding.

IV. SURVEY RESULTS

A. Team composition and background

The 25 teams that participated in the survey comprised a total of 157 people, that is around 6-7 per team on average. Of these, 79 were graduate students (50%), 30 undergraduates (19%), 23 professional engineers (15%), and 25 in the “other” category (16%), which included post-docs and advising faculty. Most teams exhibited a mix of these groups, with a heavy focus on graduates and post-graduates. The winning team (RBO, academic, Technische Universität Berlin) consisted of seven graduate students and one undergraduate, the second-place team (MIT, academic, Massachusetts Institute of Technology) consisted of five graduate students and a professional engineer, and the third-best team (Grizzly, academic/commercial, University of Oakland/Dataspeed Inc.) consisted of three professional engineers, one graduate student,

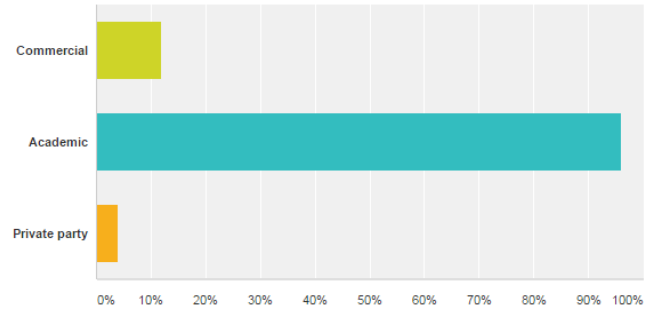


Fig. 3. Academic, non-academic and private party team composition.

and two undergraduates. Of the 25 teams, 21 were exclusively affiliated with an academic institution and one identified as a private party (Applied Robotics). Three teams were affiliated with both an academic and a commercial entity (C²M, Grizzly, Robological).

Some teams consisted of a collaboration between a robotics and a vision research group, or in case of the MIT team, a perception company. Asked about “Which skill(s) have been missing from your team? (Please think about technical skills that have not been represented at all within your team, rather than technical aspects that did not work as planned.)”, most teams identified one or more specific skill sets. We analyzed their text replies, and identified the following clusters, ordered by number of occurrences in parentheses: “computer vision” (9), “mechanical design” (4), “motion planning” (4), “grasping” (4), “force control” (3), “software engineering” (2), and “visual servoing” (2).

B. Platform

We asked each team to choose one or more hardware components from the following options: “single arm”, “multi-arm robot”, “mobile base”, “gantry”, and “other”. One team opted for a multi-robot solution that involved twelve small differential wheel robots, each equipped with a camera and small gripper, that dragged items out of the bins onto a conveyor belt. All other teams either used a single arm (9) or a multi-arm robot (15). Six teams opted for a mobile base, whereas two teams employed a gantry system to increase the workspace of their solution. Examples are PickNik who mounted a Kinova arm on a custom gantry, Grizzly which equipped a Baxter robot with a mobile base to be able to pick every bin with either the left or the right arm, using suction on one and a hand on the other, RBO who used a Barrett WAM arm on a mobile base, and Team MIT who used a single arm large enough to reach every bin without additional mobility.

For end-effectors, 36% of the teams (9) used some form of suction, whereas 84% (21) teams relied on force-closure and/or friction. That is, only four teams relied exclusively on suction, including the winner of the competition, team RBO, whereas five teams employed a combination of both. Comparing the choice of end-effector to the actual performance, we observe the following: From the 13 teams who scored better than zero points in the competition, eight teams used some form

Team	Platform	Gripper	Sensor	Perception	Motion Planing
RBO	Single arm (Barrett) + mobile base (XR4000)	Suction	3D imaging on Arm, Laser on Base, Pressure sensor, Force-torque sensor	Multiple features (color, edge, height) for detection and filtering 3D bounding box for grasp selection	No
MIT	Single arm (ABB 1600ID)	Suction + gripper + spatula	Both 2D and 3D imaging on Head and Arm	3D RGB-D object matching	No
Grizzly	Dual arm (Baxter) + mobile base (Dataspeed)	Suction and gripper	2D imaging at End-effector, 3D imaging for head, and laser for base	3D bounding box segmentation and 2D feature based localization	Custom motion planning algorithm
NUS Smart Hand	Single arm (Kinova)	Two-finger gripper	3D imaging on Robot	Foreground subtraction and color histogram classification	Predefined path to reach and online cartesian planning inside the bin using MoveIt.
Z.U.N.	Dual arm (Custom)	Suction	(respondent skipped response)	(respondent skipped response)	MoveIt RRT Planning for reaching motion and use pre-defined motion inside bin
C ² M	Single arm (MELFA) on custom gantry	Custom gripper	3D imaging on End-effector and force sensor on arm	RGB-D to classify object and graspability	No
Rutgers U. Pracsys	Dual arm (Yaskawa Motoman)	Unigripper vacuum gripper & Robotiq 3-finger hand	3D imaging on Arm	3D object pose estimation	Pre computed PRM paths using PRACSYS software & grasps using GrasPlt
Team K	Dual arm (Baxter)	Suction	3D imaging on Arm and Torso	Color and BoF for object verification	No
Team Nanyang	Single arm (UR5)	Suction and gripper	3D imaging on End-effector	Histogram to identify object and 2D features to determine pose	No
Team A.R.	Single arm (UR-10)	Suction	3D imaging on End-effector	Filtering 3D bounding box and matching to a database	No
Georgia Tech	Single arm	SCHUNK 3 finger hand	3D imaging on Head and Torso	Histogram data to recognize and 3D perception to determine pose	Pre-defined grasp using custom software and OpenRave
Team Duke	Dual arm (Baxter)	Righthand 3 finger hand	3D imaging on End-effector	3D model to background subtraction and use color / histogram data.	Klamp't planner to reaching motion
KTH/CVAP	Dual arm + mobile base (PR2)	PR2 2 finger gripper with thinner extension	3D/2D imaging on head, Tilting laser on Torso and Laser on Base	Matched 3D perception to a stored model	Move to 6 pre-defined working pose and use MoveIt to approach and grasp object

TABLE III
SUMMARY OF THE STRATEGY TAKEN BY TEAMS

of suction and only five teams relied exclusively on force-closure and/or friction. These teams were NUS Smarthand (Kinova two-fingered gripper, ranked 4th), C²M (Mitsubishi gripper, ranked 6th), GeorgiaTech (Schunk gripper, ranked 11th), Duke (Righthand Robotics, ranked 11th) and CVAP (PR2, ranked 13th). Altogether, fourteen teams used off-the-shelf end-effectors, including the PR2 gripper (3), Robotiq gripper (3), Kinova hand (2), Baxter gripper (1), Barrett hand (1), Pisa-IIT Soft hand (1), RightHand Robotics Reflex hand (1), Schunk hand (1), Weiss parallel jaw-gripper (1).

In some cases, teams combined these grippers with suction—or in the case of Plocka Plocka used the gripper to hold a suction tool on demand—combining the advantages of both approaches. In the “custom” category, teams employed various suction systems, often involving off-the-shelf “contour-adjusting suction cups”.² The MIT team combined suction with a “spatula-like finger nail”, which allowed the

robot to “scoop objects from underneath, or grasp objects that were flush against a shelf wall”. Team Grizzly used a combination of suction and grasping using Baxter’s stock suction cap in one hand and the Yale Open Hand [5] in the other. The online choice of which tool to use for each target item was based on previous performance data for each method and object. The Rutgers U. Pracsys team collaborated with a company, Unigripper, to design a custom-size vacuum gripper with a wrist-like DoF, which has multiple openings where vacuum is generated. The Unigripper tool for Rutgers was combined with a Robotiq 3-finger hand. Team Nanyang deployed a gripper that combined two suction and parallel fingers. The dual suction mechanism allows the gripper to suck items from the front, top, or side. The choice of which picking mechanism to use depends on the item pose, item position inside the bin, presence of other items, and previous performance of using the mechanisms with the items. Team CVAP modified the gripper of a PR2 to be “thinner”, allowing them more mobility inside a bin. The University of Alberta

²Text quotes are taken from the survey.

team combined a Barrett hand with a “push-pull mechanism” consisting “of a flexible metallic tape, step motor and a roll mechanism”, that allowed them to push and pull objects inside the bins.

We also asked each team “*How would you change your design?*”. We identified the following recurrent themes in the free-form answers: “Change gripper supplier/design” (8), “Use suction” (7), “Making the end-effector smaller/thinner to improve mobility” (4), “Increase workspace of the robot / add mobile base” (4), “Enhance gripper with sensor/feedback” (2), “Complement suction with gripper” (2). Minor changes include problems with payload restrictions (“gripper too heavy”) and suction systems being too weak. Team SFIT, who employed a team of twelve miniature robots placed on a separate shelf with floor heights identical to that of the shelf in which the items were placed, reported only minor design revisions, including reducing the overall number of robots.

C. Perception

We also asked each team “*What kind of sensors did you use and where were they mounted?*”, which resulted in the matrix reported in Table IV. 3D sensing in some form was employed by 22 teams, 20 of which using structured light or time-of-flight sensors, such as the Microsoft Kinect, Asus Xtion, or Intel Primesense. These sensors were mounted at various locations on the robots, most often at the end-effector (6), arm (6), and the head (8), but also on the torso (3). Several groups used more than one sensor (20 teams used a total of 23 different sensors.). Conventional 2D imaging was used by seven teams, mounted on the end-effector (4), arm (1), head (4) and torso (1). Only one team employed a laser scanner on the end-effector, whereas four teams reported using a laser scanner on a mobile base, presumably in support of navigation and alignment with the shelf rather than object detection. Two teams reported using a distance sensor in the end-effector, with one team mounting it at the robot’s head (Baxter), albeit it is unclear whether this configuration was relevant for the competition. Only one team reported using a pressure sensor at the end-effector to identify contact, while three teams mention torque/force sensing at the robot’s joints for this purpose.

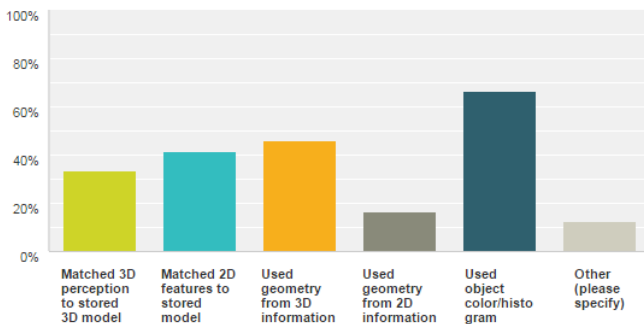


Fig. 4. “Describe your object recognition approach” (multiple answers possible).

In terms of perception algorithms, 67% of the teams (16) reported using object color and histogram data, 46% (11)

used geometrical features from 3D information, 42% (10) matched image features to those stored in a model, 33% (8) matched 3D perception data to a stored 3D model, and 17% (4) used geometrical features from 2D information (Figure 4). As for the software used, 75% (18) of the teams used the “Point Cloud Library” (PCL) [6], 67% (16) used the “Open Computer Vision Library” (OpenCV) [7], and 33% (8) report using their “own” tools (Figure 5). Other mentions (once each) include: “Object Recognition Kitchen” (ORK) [8], “SDS” [9], “Linemod” [10], “Ecto” [11] and “Scikit learn” [12], as well as proprietary software provided by Capsen Robotics (used by the MIT Team).

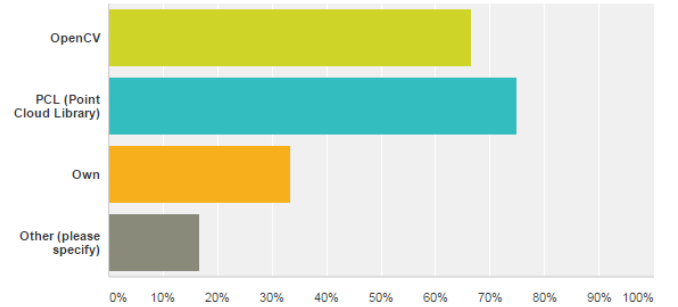


Fig. 5. “What software libraries did you use?” (multiple answers possible).

Looking at this data more closely, we observe a large diversity of approaches while also observing some common trends. We analyzed responses to the question “*Please describe your perception approach in 3–4 sentences*”. Four teams (4) indicated they used exclusively color and histogram information to identify objects, two teams (2) only used feature detection, such as SIFT [13], and another two teams (2) relied exclusively on matching 3D perception against 3D models stored in a database [14]. With a third of teams relying on only one class of algorithms, the majority of teams chose more or less complex combinations thereof. Three teams (3) combined color and histogram information with point cloud-based background subtraction exploiting the known shelf geometry. Two teams (2) instead used color information for segmentation and then used the remaining point cloud for pose estimation. Another two teams (2) used the object’s known geometry (bounding box size) for classification, with and without exploiting 2D image features. The remaining nine answers each report distinct combinations of color and 3D information including [15], [16]. One team did not reply to the question. Here, Team-K’s approach is noteworthy in that they performed identification only after picking up the object and placed it back into the bin if it was not the desired one.

In the responses to the question “*What would you do differently?*”, we identify two clusters of responses: those who would like to complement their approach with the algorithms and sensors they did not use (14), and those who would like to simplify their approach (6). One team would not make any changes and four teams did not respond to the question. Among those who want to make improvements by increasing functionality, using more 3D perception and object geometry (5), using color and histogram information (2), and exploiting

	Head	Torso	End-effector	Arm	Mobile base	Total respondents
3D imaging (Kinect, Asus, etc.)	8	3	6	6	0	20
2D imaging (camera)	4	1	4	1	0	7
Laser scanner	0	0	1	0	4	5
Distance sensor	1	0	2	0	0	3
3D imaging (tilting laser scanner)	0	2	0	0	0	2
Tactile sensor	0	0	1	0	0	1

TABLE IV

“What kind of sensors did you use and where were they mounted?”. CELLS CONTAIN THE NUMBER OF SENSORS THAT TEAMS HAVE DEPLOYED PER LOCATION. THE COLUMN “TOTAL RESPONDENTS” CONTAINS THE NUMBER OF TEAMS THAT USED EACH SENSOR MODALITY.

texture/features (2), were the common themes. Those that wish to simplify their solutions mention problems with 3rd party software packages and computational cost, which they hope to alleviate by falling back on more standard open-source products (OpenCV/PCL).

D. Planning and Control

We first asked teams “What was your basic strategy for selecting the order in which to pick the items?”. Almost all of the teams (20) implemented some kind of heuristic that took into account both difficulty of the task (presumably features like the number of items in the bin) and previous experience that allowed the designers to associate different success rates with different objects. Only three teams used simpler algorithms like sequentially moving from bin to bin or picking the object that is closest from the current end-effector position. The only team that did not implement a high-level planning algorithm to address sequencing is the multi-robot team, which employed twelve robots working in parallel.

We also asked “Did your approach rely on motion planning?” and provided choices for common software packages. 80% of all teams (20) did use motion planning, whereas 20% of teams (5) did not use any motion planning (i.e., searching for paths in a configuration space representation, as opposed to sensor-driven reactive control). Notably, the winning team (RBO) did not use motion planning. Team MIT relied on trajectory generation using the available software Drake [17], a planning and control toolbox for non-linear systems. The third place Grizzly team used very simple, home-made motion planning to align the robot with the shelf and then servo to pre-computed positions. Among the available motion planning software solutions, “MoveIt!” [18] was used by 44% of the teams (11), 28% (7) developed their own custom solutions, one team used “OpenRave” [19], and one team used “Drake” [17]. Other tools mentioned by the teams include “trajopt” [20], ROS’ JT Cartesian Controller [21], and the OMPL library [22], which was interfaced through MoveIt! or stand-alone in the teams’ custom implementations. For grasping, 96% of the teams (23) reported having developed their own, custom solution. The Rutgers U. Pracsys cited using the “GraspIt” software package [23] for generating grasping poses for the 3-finger Robotiq hand. When asked “Did you use a dynamic IK solver?”, 32% of the teams answered in the affirmative, 60% choose “No”, and 8% (2) choose “Don’t know”. Software packages used by the teams include the “Rigid Body Dynamics Library” (RBDL) [24], OROCOS with

its “Kinematics Dynamics Library” (KDL) [25], “Drake” [17], “EusLisp” [26] and “Klamp’t” [27].

“Visual servoing” was used by only 8% (2) of the teams. The other 92% (22) indicate they did not rely on visual servoing. “Force control” was used by 20% (5) of the teams, whereas 80% (20) ignored the forces induced in the robot during task execution.

When asked “What would you do differently?”, introducing more reactive control was the dominant response (8) from 22 teams responding to this question. This entails adding feedback that helps the robot ascertain that it really holds the object, as well as using force feedback and visual servoing to make up for uncertainty in sensing and actuation. Four teams (4) indicated that they wish to simplify their motion planning approach to have more direct access to path planning than MoveIt! provides. Another four teams (4) wish to improve grasping by better training grasp approaches for known objects, but also investigating techniques that exploit the environment, e.g., by pushing an object against the wall. Two teams (2) would like to improve their robot’s model fidelity and how to define tasks and constraints in this space. One team (1) indicated that using a more established architecture, such as ROS, would be desirable, and one team (1) wishes to use formal methods for controller synthesis and validation. The remaining replies wished to have done more training and fine-tuning.

E. Summary questions

We asked a couple of summary questions. First, we asked the teams to rank-order the challenges they encountered, letting them chose from six categories: “Perception” (4.52), “Grasping” (4.36), “Planning and Control” (3.75), “Mechanism Design” (3.36), “Coordinating within the team” (2.54) and “Dynamics” (2.48). The number in parenthesis is the average score, where higher scores correspond to being ranked “harder”. This data is shown in Figure 6. Looking more closely at the data, most teams ranked the categories in a similar order (similar distributions around the mean score) with the exception of team coordination, which was the biggest challenge for four teams, and the least for eleven.

We also tried to gauge the teams’ opinions on more fundamental questions by asking three questions, to which teams could answer “Do not agree”, “Somewhat disagree”, “Neutral”, “Somewhat agree”, or “Strongly agree”. 84% (21) of the teams either strongly (11) or somewhat agree (10) to the statement “Perception needs to be better integrated

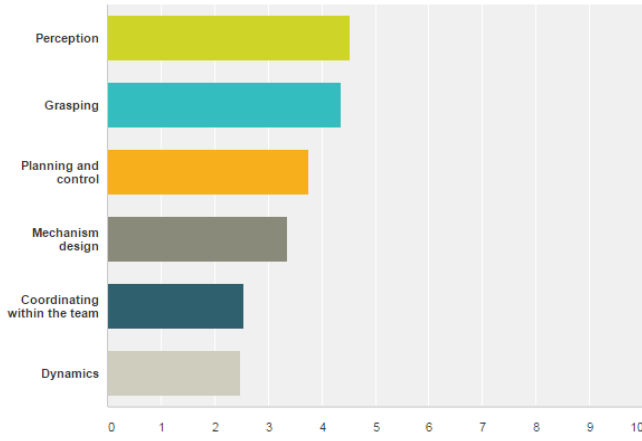


Fig. 6. “Please rank order the different aspects of the APC by their difficulty, starting with ‘most difficult’ at the top”.

with motion planning.” Two (2) teams are neutral, and two (2) teams “somewhat disagree”. 68% (17) of all teams either strongly (10) or somewhat (7) agree to the statement “*Motion planning needs to be better integrated with reactive planning.*” Six (6) teams are neutral on this statement, and two (2) do not agree. Finally, 60% of all teams either strongly (8) or somewhat (7) agree to the statement “*Development of capable, human-like robotic hands is not on the critical path for widely deploying autonomous robots.*” Five teams are neutral on this statement and another five “somewhat disagree”.

V. ANALYSIS OF SURVEY RESULTS

A. Team composition

Participants were, to a large part, graduate students, post-docs or other professionals (81%). Given that 24 of the 25 teams were from an academic environment, this number is unusual for a robotic competition—a format that is popular in senior undergraduate robotics classes [28]–[34]. We believe this to be due to the high complexity of the task, which involves mechanical design, perception, planning and grasping. It is possible that packaging a bare bones version of the competition using a widely available hardware platform (such as Rethink Robotics’ Baxter), together with design files for custom end-effectors, mounts for 3D cameras, and a more coherent software platform could create a framework for teaching a class around the Amazon Picking Challenge. Recent experience from Rutgers University indicates that it is possible to setup a semester-long project that is appreciated by students around the challenge by simplifying the problem (easier access to objects, fewer object categories) and providing access to existing software and hardware solutions (e.g., Baxter, OpenCV, etc.). Defining such an easily accessible framework and testing it across different institutions may be very valuable to the community.

We also observe that involvement from the commercial sector was minimal (three out of 25 teams). One team identified as a start-up (Robological) of which some members are still affiliated with the University of Sydney, whereas Team Grizzly and C²M are affiliated with Dataspeed Inc. and

Mitsubishi Electric Corp., respectively, which are established companies in robotics and automation. We note that none of the competitors identified as exclusively commercial, with team Grizzly involving students from Oakland University, and C²M students from Chubu University and Chukyo University. We believe, due to lack of data from the industrial sector, that the requirement to release and allow open-source access to all software packages and mechanical designs was a deterrent to commercial labs. That being said, interest from robot manufacturers was high, with multiple companies lending hardware free of charge and/or providing it to teams to use at the competition site (Barrett Technologies, Clearpath Robotics, Fanuc, Rethink Robotics, Universal Robotics, Yaskawa Motoman, UniGripper, Robotiq, ABB).

B. Mechanical design

Although the design approaches varied widely, from large, static single robot arms to mobile two-arm manipulators, it is difficult to identify a platform that is “best”. Although the challenge made use of only the middle section of bins, this was still at the working limit of many of the commercial robots. Among the top three teams, two employed a mobile platform and the other employed a single large arm. Secondary metrics, such as overall space consumption, power, or the ability to deliver objects elsewhere were not challenged by this competition. In the long run, speed will be a significant factor in many industrial applications, which may give an advantage to static arms and gantry solutions over wheeled platforms. While there was a significant number of teams in the first APC that used dual-arm manipulators, there were few attempts to pick items in parallel with the two arms, which is one way that faster picking can be achieved. Moreover, the advantages of dual-arm robots may be potentially more significant in future competitions with increased number of objects. In cases of significant occlusions, one arm can be used to clear a blocking object while another attempts to grasp the target object.

Regarding end-effector design, there is a clear trend in support of suction-based approaches. Suction alone (RBO, Team-K, Team A.R.) was proven sufficient and there were solutions that aimed to combine suction and friction-based grasping in this competition, including the two runner ups Team MIT and Grizzly. Creating constraints by grasping requires careful alignment of opposing forces on the object, whereas sucking requires only a single area of contact with the suction orifice. Unlike friction-based grasping, sucking an object minimizes both translational and rotational degrees of freedom, which makes the approach robust against wrenching forces. Many teams with a vacuum-based approach used an off-the-shelf vacuum cleaner or suction cup, instead of industrial setups. Some traditional suction mechanisms used in the industry can require careful placement to maintain vacuum, whereas vacuum cleaners continuously pull the air, which may work even if there is an opening between a gripper and an object, due to a complex surface or unexpected motion of the arms. This more robust attachment comes at the cost of much longer decay times when releasing an object. A drawback of suction-only approaches are their poor ability to manipulate an

object; this capability was not prominent in the APC so far, however future contests are expected to have more populated bins that may require more flexible manipulation and object rearrangement [35], or a more explicit exploitation of the environment [36], [37]. The value of a combination of suction and grasping also becomes clear when considering objects like the metal-mesh pencil holder or the foam balls, which are difficult to suck. With only two out of 25 items having this property, however, this first competition encouraged using a less complex suction-only solution than dealing with the challenges that a combined approach entails.

Most teams would re-design or improve their grasping capabilities. Half of the 14 teams that did not use suction would change their design to include suction. Almost a third of the teams (8), would either change the gripper they were using or dramatically improve it to become more dexterous, thinner and more light-weight.

The most unique mechanical design, Team SFIT, involved twelve miniature mobile robots. This approach was among the many teams that did not successfully score any points, which makes it difficult to compare its merits against other designs quantitatively. Philosophically, however, their unconventional approach could offer a variety of benefits. Mobile robots that are individually smaller than most grippers used in the competition could possibly reach far into the corners of each bin, while their number increases robustness to mechanical breakdown. On the other hand, smaller robots may not have sufficient strength to extract heavy or the flexibility to deal with stacked or occluded items. Furthermore, an increased number of mechanical components may decrease the robustness of the overall solution.

C. Perception

With 20 teams employing structured light for 3D perception, this technology was by far the most used sensing modality. Although perception turned out to be a key challenge in this competition—with many groups working around the grasping problem by employing suction—it is not easy to identify a correlation between the teams’ background in perception and their performance in the competition. Indeed, all top three teams identify vision as one of their key challenges and note insufficient background in their groups. At the same time, groups with a known track-record in computer and machine vision were not as successful. A reason for this might be the maturity of open source tools such as PCL and OpenCV, which allowed most groups to cover their basic sensing needs quickly. Research-grade software provided often only marginal improvements while it lacked the maturity of well-maintained open-source projects. In future competitions, as the item density increases in the bins, more advanced vision software may play a more differentiating role.

To assist the development of visual perception solutions for solving warehouse pick-and-place tasks, a new rich data set has become available that is devoted to this type of challenges [16]. The publicly available data set includes thousands of RGBD images and corresponding ground truth data for 3D object poses for the items used during the first Amazon Picking Challenge at different poses and clutter conditions.

Only a few teams expressed a desire to enhance their gripper with sensors. This is surprising, as only three of the presented solutions actually had any sort of feedback in their grippers, and only two used it. Employing a pressure sensor was integral to RBO and MIT team’s suction capabilities, and Team-K read the control board of the vacuum cleaner to detect the sucking status, whereas Duke did not use the sensors provided by the RightHand Robotics ReFlex hand. Team MIT used force feedback in the opening of their parallel-jaw gripper to detect contact with the shelf and the objects. Other teams used visual and force sensing to detect whether a grasp was actually successful or to re-adjust grasping. One reason for this might be that the community as a whole has very little experience with in-hand sensing due to the lack of availability of hands with integrated sensors and algorithms that use this information during grasping. Indeed, there are only a small number of such systems out there, and only few are commercially available [38].

D. Planning and Control

Most teams employed a high-level task planning framework that targeted maximizing the expected score, many of which went for difficult objects that were likely to lead to penalties for dropping or picking the wrong item. While this strategy was appropriate for a game, a production setting would require all items to be picked. For such an environment, it would be more interesting to find policies that maximize throughput by minimizing trajectories (which only one team did) or exploiting the ordering of items in a bin.

Surprisingly, many of the teams, including the winning team, did not make use of motion planning. Here “motion planning” refers to a deliberative algorithm that uses environment and robot models to generate a collision-free trajectory before executing it. It was possible to build successful systems without motion planning because the real-world scenario on which the competition was based was designed for easy picking by humans. Easy access to all of the bins and easy access to the objects within each bin effectively eliminated the need for complex motion planning around obstacles. As a result, reactive control approaches were sufficient to generate appropriate motions while avoiding obstacles within the shelf.

While a large number of teams used MoveIt!, an integrated motion planning and visualization framework, none of the top three performers used such software. This may suggest—like in the case of perception software—that prepackaged toolkits for these complex behaviors help teams to get started rapidly [18], but do not necessarily help them access and improve lower-level functionality in an equally easy manner. Generally, MoveIt! and other pre-packaged motion planning software solutions have three problems: 1) the robot is not allowed to exploit contact, 2) uncertainty is not taken into account during planning, and 3) incorporation of sensor-based feedback is not straightforward. This approach is in contrast with the winning team’s architecture that consisted of a hybrid automaton that connected a variety of feedback controllers [39] with event-based state transitions. Here, sensors included object position provided by the camera, contact via pressure

sensors, and actual torques. Since motion planning appears important in general in geometrically more complex scenes to navigate around obstacles, a potentially important topic of future research is how to better integrate planning with feedback to make up for inaccurate sensing and actuation. There currently exist no high-level tools that combine these approaches in a user-friendly way. The community would greatly benefit from manipulation planning tools that better support reasoning over contacts, sensor-based feedback and uncertainty.

Regarding grasp planning, an overwhelming majority of teams used custom approaches, which may appear surprising at first. To explain this, we first note that about 20% of teams opted for suction over grasping, which dramatically simplifies the problem by reducing it to choosing surfaces that are flat and planning to reach them. However, this level of customization is also indicative of more fundamental problems, namely, difficulties in generalizing the grasping problem across mechanical platforms, and difficulties in incorporating uncertainty and environmental context into grasp planning. The output of “GraspIt!” designates an end-effector and finger pose for a given object geometry that optimizes some wrench-based grasp metric. This metric ignores environmental context, reachability, pose uncertainty, and nonprehensile strategies, such as pushing, that may be more important than robustness to disturbance wrenches. Further tipping the balance toward custom solutions is that current trends in manipulation include shifting some of the required reasoning into end-effector compliance [5], [40] and using under-actuated systems [37], [41]–[43]. As a result, many objects can be grasped using simple rules, such as attempting a power grasp along the medial axis of the object. Compliance can play an important role even in conjunction with suction as indicated by the Unigripper’s design with the Rutgers U. Pracsys team, where a foam is introduced between the object and the suction openings so as to help to adapting to the surface of an object and forming vacuum by pressing on the object.

It is important to note that the APC shelves are relatively uncluttered compared to the shelves encountered by human pickers, which may have dozens of objects in close contact. This simplification may have biased the teams’ choices of grasping strategies toward solutions like suction and standard parallel-jaw grippers, whereas a more complex arrangement of objects may motivate the use of human-like dexterity and grasp planning capabilities.

There appears to be a division between control-centric and planning-centric approaches to problems like the APC. The two top solutions made extensive use of visual servoing and force control. They also did not involve “grasping”, i.e., explicit reasoning regarding grasping poses, and only a very limited amount of “motion planning”, i.e., collision-free planning in a configuration space representation. Across other teams, visual servoing and force control techniques were sparsely used, and furthermore only two teams identified these techniques to have been absent in their approaches. By contrast, only four teams outside of the top two failed to implement either grasping or motion planning. Although it is tempting to draw general conclusions based on this data,

the third-place team (Grizzly) did not use any reactive control schemes, but relied on motion planning and SLAM (Hector SLAM ROS package [44]) to localize and move a mobile Baxter robot in front of the appropriate bin. It is therefore unclear what the “best” approach is, albeit the strategy of using reactive control to compensate for inaccurate sensing and actuation of an underlying deliberative architecture appears to be powerful.

Indeed, when asked what to improve, there was a clear desire to include more reactive control to make up for deficiencies with the sense-plan-act model. The challenge participants were also not content with the abstraction level that prepackaged software solutions like MoveIt! provided. On the one hand, teams wished for the ability to model their robot hardware more easily and have simple ways to provide tasks and constraints, much like the way MoveIt! [18] and OpenRave [19] provide. On the other hand, the tools are not perfect yet, are difficult to debug, and have a high learning curve should a solution require the team to make changes “under the hood” of such tools. A possible solution here might be not only to continue to improve these tools, but abstract their lower-level functionality into a higher level language, making their inner workings more accessible, and making it easier to attach arbitrary sensing, reactive controllers and logic to the trajectories they generate.

VI. DISCUSSION

An important conclusion to draw from the APC is that recent developments in robotics have the potential of substantially increasing the degree of automation in warehouse logistics and order fulfillment in the near future. Many efforts to broaden the impact and applicability of robotics in industry beyond factory automation have faced substantial challenges. The kind of warehouse logistics addressed in the APC, however, can believably be automated using existing or near-future technologies and potentially faster than many other target applications of robotics. It therefore seems worthwhile to continue the APC in order to foster the exchange between the robotics community and relevant industrial partners.

Addressing warehouse logistics and order fulfillment in industrial settings will probably still require substantial scientific progress. As was outlined above, some of the standard solutions, such as motion planning or complex hands, were not necessary to succeed in the first instantiation of the APC. This may point to the fact that the space of possible solutions is not fully explored yet and that simple approaches may be a more promising route for critical applications despite the importance of providing general-purpose robots. It is possible that the focus on component technologies, such as 3D object pose estimation, control, motion planning, grasping, etc., has not allowed the community to study integrated solutions.

A more comprehensive treatment of robotic challenges, in terms of their software, hardware and algorithmic components, appears necessary. In particular, in this competition teams were faced simultaneously with a hardware and a software design problem. This allowed to simplify the complexity of the software development process by modifying hardware, or

vice versa. For example, the use of vacuum grippers sidestepped the challenging problems of grasp planning and in-hand manipulation, which are more critical when using human-like hands. Thinner end-effectors simplified the process of computing collision-free paths in tight spaces. Integrating sensor-feedback in the control process was used successfully by several teams to compensate for less precise actuators, such as mobile bases or lower-cost robot arms. This pattern highlights the continued need for cross-disciplinary collaboration in robotics between hardware, software and algorithmic researchers to build task-specific, robust integrated systems.

The APC showed once again that system integration and development remain fundamental challenges in robotics. When a working system consists of dozens, if not hundreds, of independent components and the failure of each of these components can lead to catastrophic failure of the overall system — as witnessed during the competition — the focus is shifted from scientific questions towards software and hardware development and testing practices. As a community, it is critical to decide whether such insights should be equally worthy of publication as technical advances. It also suggests a need for a common and accepted knowledge-base of how to build, test, and deploy integrated robotic solutions. It is arguable whether this expertise already exists in industry, where system complexity might be addressed in ways inappropriate for research in robotics.

A. *Moving Forward*

While the first APC laid a foundation for testing competing solutions to order fulfillment, the manipulation problem was greatly simplified relative to real-world warehouse scenarios. In particular, we discuss three axes in which the complexity of APC can gradually increase to get closer to a real scenario.

Object Density. The cost of land and indoor spaces stresses the need for packing more items into smaller spaces, shelves and bins. This creates the need for picking, placing, and manipulation in tight spaces and for tightly arranged objects.

In the APC 2015, the objects in the bins were arranged side by side and lightly packed, far from what would be expected in a warehouse. Tight object arrangement has important consequences for the manipulation strategies employed, and for how the robotic system interacts with objects and storing structures. Extracting a free-standing book from a bin and extracting a book that is wedged between other books are very different manipulation problems. While the first can be solved in the pick-and-place paradigm (i.e., reach, grasp, extract), the second is badly suited to standard grasp planning techniques. The desired contact surfaces are rarely sufficiently exposed, leading to a different manipulation problem where the grasp is only the last stage of a longer process that drives the object into the gripper and where interactions with the environment play a critical role.

Sparse bins allow methods that avoid contact with other obstacles to be successful. In APC 2015, once an object was grasped (whether by suction or by fingers), it could be directly extracted. However, more tightly-packed bins may require brushing obstacles aside in order to reach and retrieve the

target object, as well as sliding the object along the bottom or sides of the bin. The need to manipulate in contact may radically change both the software and hardware methods used in the APC (e.g., shifting the emphasis toward compliant control and compliant hardware), and the level of sensing required at the point of the manipulation (e.g., tactile and in-hand vision sensors). A key challenge to overcome in tightly-packed bins is to perform the necessary manipulation under limited sensing and poor prior knowledge of the environment.

Speed. Human pickers in Amazon warehouses pick items at an approximate rate of 5-10 seconds per item. Reaching that speed with an automated solution is likely as much a research problem as it is an engineering one, requiring fine-tuning computations of all algorithms as well as optimizing all robot motions. It is therefore not a reasonable goal for APC to expect that average rate. Improvements in speed are nevertheless a direction in which the challenge could propel us forward, if this technologies are to become useful in the near future. With the danger of leading the community to premature optimization rather than out-of-the-box innovation, speed can be used as one measure of progress, potentially guiding the selection of robotic mechanisms as well as algorithmic solutions.

Reliability. Finally reliability is key to any industrial operation, and the rate errors showed even by the top teams were far from the expectations of automation companies. Errors such as dropped items, destroyed items, or miss-classified items should continue to be penalized. An interesting variation to consider is the type of error that occurs but that it is also detected and correctly identified. That is an type of error that, under the right circumstances might be acceptable, and could have a smaller penalty.

Tolerance to miss-calibrations plays a key role in the reliability of a system. During APC 2015 it was possible to off-line and accurately calibrate the relative location of the shelf with respect to a static robot. This simplifies manipulation and is not representative of the real problem. Promoting solutions that are more robust to calibration errors should allow progress towards more flexible systems that can be used in less structured environments. These include warehouses, but also other applications such as home-assistive robots, which will frequently have to deal with manipulation in tight spaces.

In recent years, it has been said that grasping is a solved problem. That is in part due to a bias toward “table-top” manipulation, the DARPA ARM Project being a prominent example. Scenarios with isolated objects without many environmental constraints lend themselves to the grasp-planning approach. APC points to a different problem, one where the key role is not played by the grasp but by the reach and retrieve actions.

While many robotics researchers participated in the APC with great enthusiasm and obtained in return significant insights and advances, there were also critical voices in the community. Several researchers raised the question whether it is appropriate for a technology-oriented company with

significant resources, such as Amazon, to divert the work of publicly-financed research labs towards a research agenda beneficial to the company, while investing a disproportionately small amount. Similar arguments were made with the DARPA Robotics Challenge and are probably inherent to the idea of funded challenges.

VII. CONCLUSION

The APC contest was an exciting showcase of the application of advanced research to a real-world problem. Modern advances in the robotics field are opening up a new set of tasks that are far more nuanced and dynamic than the rote industrial applications of the past. However, it is clear that improvements and breakthroughs are still required to reach human-like levels of speed and reliability in such settings. A human is capable of performing a more complex version of the same task at a rate of ~ 400 sorts/hour with minimal errors, while the best robot in the APC achieved a rate of ~ 30 sorts/hour with a 16% failure rate. The challenge was an interesting measuring stick that illustrated the maturity of the various components and their readiness to transition into industrial applications.

It is a credit to the robotics community that many of the open-source projects from the robotics world made up the foundation of the APC systems. Developing a system capable of handling such a challenge in a matter of months would be unthinkable without quality tools and applicable research. It is important to note, however, the valuable feedback in places where these tools were difficult to integrate into a full solution, or proved challenging to modify to provide a robust solution to specific tasks.

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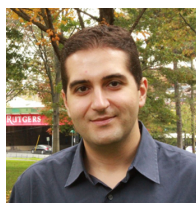
REFERENCES

- [1] J. Anderson, J. Baltes, and C. T. Cheng, "Robotics competitions as benchmarks for AI research," *The Knowledge Engineering Review*, vol. 26, no. 01, pp. 11–17, 2011.
- [2] P. Baker and Z. Halim, "An exploration of warehouse automation implementations: cost, service and flexibility issues," *Supply Chain Management: An International Journal*, vol. 12, no. 2, pp. 129–138, 2007.
- [3] R. D'Andrea, "Guest editorial: A revolution in the warehouse: A retrospective on Kiva systems and the grand challenges ahead," *IEEE Transactions on Automation Science and Engineering*, vol. 4, no. 9, pp. 638–639, 2012.
- [4] P. R. Wurman, R. D'Andrea, and M. Mountz, "Coordinating hundreds of cooperative, autonomous vehicles in warehouses," *AI magazine*, vol. 29, no. 1, p. 9, 2008.
- [5] R. R. Ma, L. U. Odhner, and A. M. Dollar, "A modular, open-source 3d printed underactuated hand," in *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, pp. 2737–2743, IEEE, 2013.
- [6] R. B. Rusu and S. Cousins, "3d is here: Point cloud library (pcl)," in *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, pp. 1–4, IEEE, 2011.
- [7] G. Bradski and A. Kaehler, *Learning OpenCV: Computer vision with the OpenCV library*. "O'Reilly Media, Inc.", 2008.
- [8] R. c. Willow Garage, "ORK: Object Recognition Kitchen." https://github.com/wg-perception/object_recognition_core.
- [9] B. Hariharan, P. Arbeláez, R. Girshick, and J. Malik, "Simultaneous detection and segmentation," in *European Conference on Computer Vision (ECCV)*, 2014.
- [10] S. Hinterstoisser, C. Cagniat, S. Ilic, P. Sturm, N. Navab, P. Fua, and V. Lepetit, "Gradient Response Maps for Real-Time Detection of Texture-Less Objects," *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, vol. 34, no. 5, pp. 876–888, 2012.
- [11] R. c. Willow Garage, "Ecto — a c++/python computation graph framework." <http://plasmodic.github.io/ecto/>.
- [12] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, et al., "Scikit-learn: Machine learning in python," *The Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [13] T. Tuytelaars and K. Mikolajczyk, "Local invariant feature detectors: a survey," *Foundations and Trends® in Computer Graphics and Vision*, vol. 3, no. 3, pp. 177–280, 2008.
- [14] A. Aldoma, Z.-C. Marton, F. Tombari, W. Wohlkinger, C. Potthast, B. Zeisl, R. B. Rusu, S. Gedikli, and M. Vincze, "Point cloud library," *IEEE Robotics & Automation Magazine*, vol. 1070, no. 9932/12, 2012.
- [15] Y. Domae, H. Okuda, Y. Taguchi, K. Sumi, and T. Hirai, "Fast grasability evaluation on single depth maps for bin picking with general grippers," in *Robotics and Automation (ICRA), 2014 IEEE International Conference on*, pp. 1997–2004, IEEE, 2014.
- [16] C. Rennie, R. Shome, K. E. Bekris, and A. F. D. Souza, "A dataset for improved rgbd-based object detection and pose estimation for warehouse pick-and-place," in *IEEE International Conference on Robotics and Automation (ICRA), 2016*, (Stockholm, Sweden), 2016.
- [17] R. Tedrake, "Drake: A planning, control, and analysis toolbox for nonlinear dynamical systems," 2014.
- [18] D. Coleman, I. Sucan, S. Chitta, and N. Correll, "Reducing the barrier to entry of complex robotic software: a moveit! case-study," *Journal of Software Engineering in Robotics, Special issue on Best Practice in Robot Software Development*, vol. 5, no. 1, pp. 3–16, 2014.
- [19] R. Diankov and J. Kuffner, "Openrave: A planning architecture for autonomous robotics," *Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RI-TR-08-34*, vol. 79, 2008.
- [20] J. Schulman, J. Ho, A. Lee, I. Awwal, H. Bradlow, and P. Abbeel, "Finding locally optimal, collision-free trajectories with sequential convex optimization," in *Robotics: Science and Systems*, vol. 9, pp. 1–10, Citeseer, 2013.
- [21] J. Nakanishi, R. Cory, M. Mistry, J. Peters, and S. Schaal, "Comparative experiments on task space control with redundancy resolution," in *Intelligent Robots and Systems, 2005.(IROS 2005). 2005 IEEE/RSJ International Conference on*, pp. 3901–3908, IEEE, 2005.
- [22] I. Sucan, M. Moll, L. E. Kavraki, et al., "The open motion planning library," *Robotics & Automation Magazine, IEEE*, vol. 19, no. 4, pp. 72–82, 2012.
- [23] A. T. Miller and P. K. Allen, "Graspit! a versatile simulator for robotic grasping," *Robotics & Automation Magazine, IEEE*, vol. 11, no. 4, pp. 110–122, 2004.
- [24] M. Felis, "RBDL: Rigid Body Dynamics Library." <http://rbdl.bitbucket.org/>.
- [25] H. Bruyninckx, "Open robot control software: the orocos project," in *Robotics and Automation, 2001. Proceedings 2001 ICRA. IEEE International Conference on*, vol. 3, pp. 2523–2528, IEEE, 2001.
- [26] T. Matsui and M. Inaba, "EusLisp: An Object-Based Implementation of Lisp," *Journal of Information Processing*, vol. 13, no. 3, pp. 327–338, 1990.
- [27] K. Hauser, "Klamp't: Serious tools for serious contact," 2015.

- [28] L. B. Almeida, J. Azevedo, C. Carneira, P. Costa, P. Fonseca, P. Lima, A. F. Ribeiro, and V. Santos, "Mobile robot competitions: fostering advances in research, development and education in robotics," 2000.
- [29] C. Messom, D. Carnegie, P. Xu, S. Demidenko, and D. Bailey, "Robotic competitions: Motivation for engineering programmes," in *Proceedings of the Ninth New Zealand Electronics Conference, Dunedin, Dunedin, New Zealand*, pp. 55–60, Citeseer, 2002.
- [30] D. Tougaw and J. D. Will, "Integrating national robotic competitions into multidisciplinary senior project courses," in *Proceedings of the American Society for Engineering Education Illinois/Indiana Conference*, Citeseer, 2005.
- [31] M.-T. Chew, S. Demidenko, C. Messom, and G. S. Gupta, "Robotics competitions in engineering education," in *Autonomous Robots and Agents, 2009. ICARA 2009. 4th International Conference on*, pp. 624–627, IEEE, 2009.
- [32] J. Pastor, I. González, and F. Rodríguez, "Participating in an international robot contest as a way to develop professional skills in engineering students," in *Frontiers in Education Conference, 2008. FIE 2008. 38th Annual*, pp. S3F–9, IEEE, 2008.
- [33] K. Nagatani, A. Kushleyev, and D. D. Lee, "Sensor information processing in robot competitions and real world robotic challenges," *Advanced Robotics*, vol. 26, no. 14, pp. 1539–1554, 2012.
- [34] N. Correll, R. Wing, and D. Coleman, "A one-year introductory robotics curriculum for computer science upperclassmen," *IEEE Transactions on Education*, no. 99, pp. 1–1, 2012.
- [35] A. Krontiris and K. E. Bekris, "Dealing With Difficult Instances Of Object Rearrangement," in *Robotics: Science and Systems (RSS)*, (Rome, Italy), 2015.
- [36] N. Chavan Dafle, A. Rodriguez, R. Paolini, B. Tang, S. S. Srinivasa, M. A. Erdmann, M. T. Mason, I. Lundberg, H. Staab, and T. A. Fuhlbrigge, "Extrinsic Dexterity: In-Hand Manipulation with External Forces," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2014.
- [37] C. Eppner, R. Deimel, J. Alvarez-Ruiz, M. Maertens, and O. Brock, "Exploitation of environmental constraints in human and robotic grasping," *The International Journal of Robotics Research*, vol. 34, no. 7, pp. 1021–1038, 2015.
- [38] Y. Tenzer, L. P. Jentoft, and R. D. Howe, "The feel of mems barometers: inexpensive and easily customized tactile array sensors," *Robotics & Automation Magazine, IEEE*, vol. 21, no. 3, pp. 89–95, 2014.
- [39] O. Khatib, "A unified approach for motion and force control of robot manipulators: The operational space formulation," *Robotics and Automation, IEEE Journal of*, vol. 3, no. 1, pp. 43–53, 1987.
- [40] A. M. Dollar, L. P. Jentoft, J. H. Gao, and R. D. Howe, "Contact sensing and grasping performance of compliant hands," *Autonomous Robots*, vol. 28, no. 1, pp. 65–75, 2010.
- [41] G. A. Kragten and J. L. Herder, "The ability of underactuated hands to grasp and hold objects," *Mechanism and Machine Theory*, vol. 45, no. 3, pp. 408–425, 2010.
- [42] M. T. Mason, A. Rodriguez, S. S. Srinivasa, and A. S. Vazquez, "Autonomous Manipulation with a General-Purpose Simple Hand," *The International Journal of Robotics Research*, vol. 31, no. 5, pp. 688–703, 2012.
- [43] R. Deimel and O. Brock, "A novel type of compliant and underactuated robotic hand for dexterous grasping," *International Journal of Robotics Research*, 2015. Online First.
- [44] S. Kohlbrecher, J. Meyer, O. von Stryk, and U. Klingauf, "A flexible and scalable slam system with full 3d motion estimation," in *Proc. IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR)*, IEEE, November 2011.



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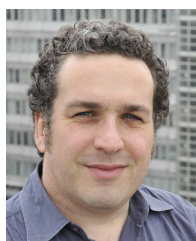


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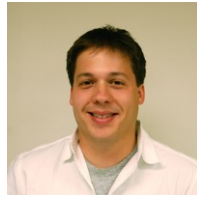
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